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Machine Learning in Neuroimaging for Diagnosis of Major Depressive Disorder

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ABSTRACT

Is machine learning an effective diagnostic tool to identify the presence of major depressive disorder in a patient? Major depressive disorder (MDD) is a common mood disorder, distinguished by prolong emotional distress and dysfunction in normal activities, yet its current diagnosis still depends on subjective interpretation of clinical interviews and self-reported symptoms. Not only are these prevalent methods susceptible to inconsistent diagnoses, the lack of clear boundaries in present diagnostic criteria to evaluate MDD also further magnifies the need for objective diagnostic tools in clinical environment. One of those methods explored by psychologists is the application of machine learning in neuroimaging techniques. Due to its analytical prowess, machine learning has become popular in psychological research to understand and discover biomarkers in illnesses. This literature review aims to evaluate the effectiveness of different machine learning models and neuroimaging in classifying MDD patients before discussing some of the major setbacks faced by researchers and the suggested solutions for overcoming these barriers to clinical application.

INTRODUCTION

Being complex and heterogeneous in nature, major depressive disorder has been challenging the concept of illness since its founding, posing a conundrum regarding accurate diagnosis and treatment. However, with the rise of machine learning, scientists are beginning to reach a breakthrough in understanding the characteristics of depression; and through advanced computational models, new methodologies can be pioneered.

Major depressive disorder (MDD) is a common multifactorial disorder characterized by a two-week discrete episode of recurrent low mood, impaired cognitive functions, and other depressive symptoms [1]. It affects around 6% of adults every year [2] and is a major contributor to the overall global burden of disease [3]. Heritability and environmental factors, such as undergoing traumatic events, are associated with an increased risk of developing the disorder [4-6]. Changes in brain structure and function may also indicate its manifestation [7]. Nevertheless, due to its heterogeneity, the exact pathophysiology remains to be fully clarified, and hence limit the prevalent diagnosis of MDD to clinical interviews and self-reported symptoms [8, 9]. In the process of finding more objective diagnostic tools, psychologists began to adopt machine learning in neuroimaging.

In early neuroimaging studies, statistical parametric mapping was used to perform voxel-based comparisons between groups to construct spatial maps of brain structure and function [15], but such mass-univariate inferences are confined to focal changes in brain morphology which do not reveal subtle and widespread interactions between brain networks [16]. As a consequence, machine learning approaches are integrated into neuroimaging to provide multivariate solutions that demonstrate greater sensitivity and more reliable predictions than univariate methods, thus enabling the development of imaging brain signatures at the individual level [17, 18]. Among the most successful machine learning techniques, support vector machines (SVMs) [21-23], random forests (RF) [24-30], and deep learning (DL) [31-33] have become exceedingly popular for neuroimaging analysis in recent years.

The purpose of this study is to review methodologies of past research that adopt machine learning in neuroimaging to classify major depressive disorder from healthy controls or other mood disorders, and discuss some of the challenges faced by the researchers.

LITERATURE REVIEW

Major Depressive Disorder

According to the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5), major depressive disorder (MDD) is defined as a two-week episode of experiencing at least five out of nine depressive symptoms, involving depressed mood or loss of interest, for most of the day, nearly every day [1]. It is required that symptoms attributable to substance use and other psychotic disorders are excluded from the criteria [1]. Although DSM-5 does not categorize MDD in terms of severity level [1], the severity of MDD can still be evaluated with the aid of rating depression scales, such as the Hamilton Depression Rating Scale (HDRS) [10].

After interviewing samples of adults going through major depressive episodes from 18 countries, Bromet, E. et al. (2011) approximated that MDD affects around 6% of the global adult population every year, and at least 10% have ever had MDD at some point in life [2]. It was also found by the same study that women are twice as likely as men to be affected by MDD [2]. In another research, Kovacs, M. et al. analyzed the course of MDD from childhood to young adult, spanning across two decades [11]. The results revealed that, even though recovery rates across MDD episodes are substantially high, more than 70% of those recovered experienced further episodes, but no temporal trends in episode duration or recurrence risk are found [11]. Furthermore, in the Global Burden of Disease Study (2013), MDD was among the leading causes of disability [3].

MDD is a heterogeneous and pleomorphic illness resulting from both genetic and environmental factors [4-6]. The genetic heritability of MDD, analyzed by Sullivan, P.F. et al. (2000) and Kendler, K.S. et al. (2006), was estimated to be around 40% with higher correlations associated with first-degree relatives and women, but the specific genetic loci that contribute to disease susceptibility are yet to be established [4,5]. Childhood abuse, further elucidated by Li, M. et al. (2016), also play a significant role in increasing the risk of MDD [6]. Nevertheless, the exact mechanisms of how genetic and environmental aspects of MDD interact still remain incomplete [4-6].

One of the pathophysiology of MDD involves abnormalities in brain structure and functions, particularly distributed across cortical, subcortical, and brainstem regions, according to a study by Pandya, M. et al. (2012) [7]. In the cortical region, it is associated with impaired metabolism and perfusion in the prefrontal cortex, abnormalities in the anterior cingulate cortex, and increased insular sensitivity in response to negative stimuli, which cause executive dysfunctions and poor mood regulations and stress response [7]. Smaller hippocampal and amygdala core volumes, as well as abnormal activation of the amygdala in the subcortical region, are also implicated in MDD, although the relative volumetric changes vary across individuals [7]. In the brainstem region, the exact role of the striatum in the presence of MDD is still inconsistent with other findings, but a decreased production of the neurotransmitter serotonin in the raphe nucleus is evident [7].

Currently, prevalent psychiatric practices are based on clinical interviews and self-reported symptoms [8]. However, according to Smith, K.M. et al. (2013), these long-standing methods are highly prone to subjectivity and do not always provide consistent results, leading to misdiagnoses at times [8]. Although laboratory methods such as the dexamethasone suppression tests exist, they yield inaccurate clinical performance and are not widely used among clinicians [8]. In addition, the diagnostic criteria of MDD in DSM-5, which aid in the evaluation of depression, lack discrete boundaries between similar disorders and clear-cut psychometric information to assist clinical decision-making [9]. In their article, Uher, R. et al. (2014) asserted that DSM-5 field trials returned the lowest reported reliability for the MDD diagnosis compared with the previous editions, and called for the need to address these shortcomings in present assessment tools [9].

The general categories of MDD treatments include psychotherapy and pharmacotherapy [12, 13]. Some of the most effective psychological interventions are cognitive behavioral therapy, which aims to help patients identify

and change negative thinking patterns, and interpersonal therapy, which focuses on establishing satisfying relationships to help relieve depressive symptoms [12]. Antidepressants, such as selective serotonin reuptake inhibitors and serotonin-norepinephrine reuptake inhibitors, are also another efficacious form of treatment [13].

Machine Learning in Neuroimaging

Neuroimaging allows clinicians to view patients' brains without surgical interventions [14]. Discrimination of MDD from healthy control or other mood disorders and identification of depression subtypes have been performed using neuroimaging techniques, including magnetic resonance imaging (MRI), positron emission tomography (PET), magnetoencephalography (MEG), and electroencephalography (EEG) [14]. In their study, Dunlop, B.W., & Mayberg, H.S. (2017) have summarized some of the neuroimaging techniques associated with mood disorders, as illustrated in Figure 1 [14].

Prior to the application of machine learning (ML), the majority of traditional neuroimaging studies of brain disorders are based on mass univariate methods [15, 16]. Massive univariate methods (univariate means involving one variable) emerged during the 1990s, particularly the use of voxel-based statistics in statistical parametric mapping (SPM) to distinguish focal differences in brain morphology between groups [15]. Developed by Friston, K.J. et al. (1994), SPM makes regionally specific inferences by measuring each voxel individually [15]. However, according to Davatzikos, C. (2004), such a method is largely restricted to linear statistics, which doesn't capture the nonlinear characteristics of the brain, such as the diffused interactions between brain networks.

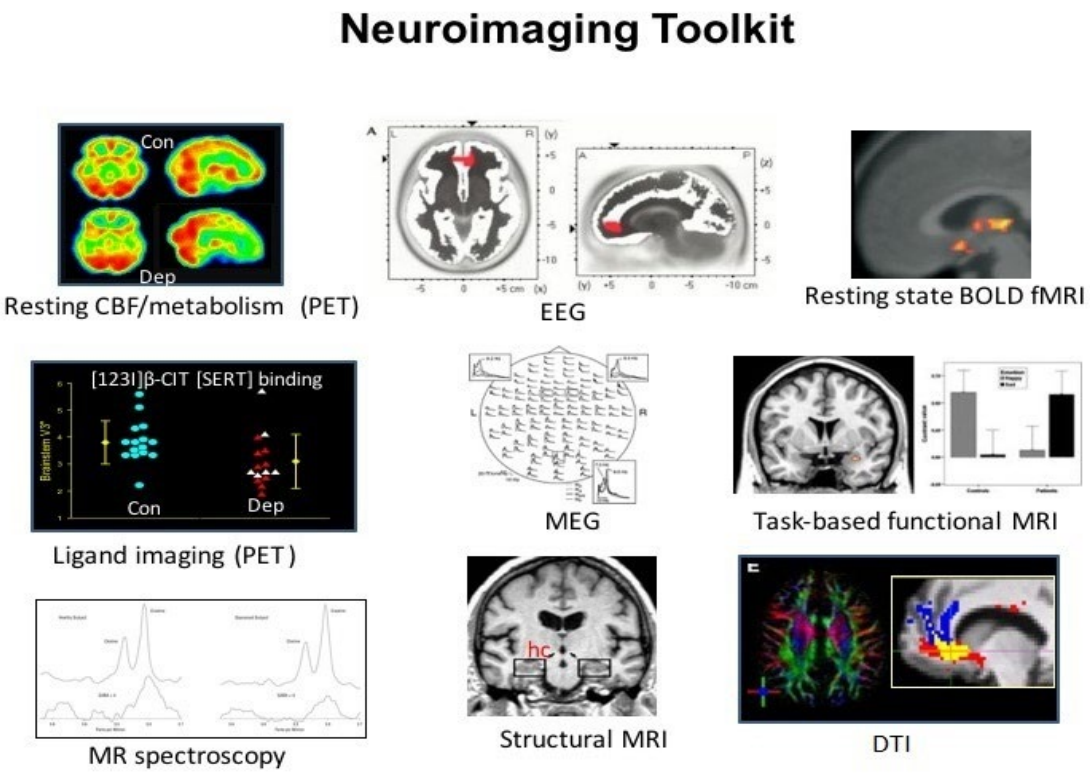

Figure 1. The seven neuroimaging forms associated with mood disorders, taken from Dunlop, B.W., & Mayberg, H.S. (2017) [14].

This leads to the application of ML in neuroimaging to improve accuracy by providing greater reliability and sensitivity to changes in functional connectome [17]. The integration of multivariate pattern classification enables more powerful information to be detected at an individual level, as demonstrated in a study by Yoo, K. et al. (2019)

where multivariate measures could identify people using their brain connectivity patterns at a mean rate of 97% in shorter time span whereas univariate methods were only successful with 58% rate [17]. Although currently challenging, ML has great potential to investigate brain imaging biomarkers to confirm the diagnosis of MDD, especially in early depressive episodes, to assist in selecting effective timely treatment for MDD patients [18].

Machine learning (ML) is defined as a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data or perform decision making under uncertain conditions [19]. Over the last few decades, the application of ML algorithms in neuroimaging data analysis has grown increasingly [20].

Among them, the support vector machine (SVM) became one of the most powerful pattern classification methods [21]. According to Lao, Z. et al. (2004), the SVM focuses on modeling minor morphological differences between two groups instead of the general differences, and hence can be effective in small sample groups when major differences do not influence the results [21]. For that reason, the vast majority of past studies reviewed by Patel, M.J. et al. (2016) used SVM in MRI to predict depression diagnosis and frequently achieved an accuracy score of 70% and above [22]. There is variability in using non-linear and linear methods [22] because, in some cases where the number of samples are substantially smaller than the number of features, nonlinear methods do not significantly affect the final results and hence better to use linear methods to avoid complexities and overfitting [23]. However, as explained in Hsu, C.W. et al. (2003) SVMs do not generally function well in large datasets with many features, so reducing the features or choosing the right kernel functions in SVM algorithms are crucial in obtaining desirable results [23].

Another method that gained popularity is the random forests (RF), which, as explained in Breiman, L. (2001), are a combination of uncorrelated and randomly generated decision trees that vote for the most popular class to produce the output [24]. This method tends to have good generalization and reduces overfitting as more individual trees are added, and therefore is robust to noise in datasets [24]. Thus far, there has been no study that investigates RF algorithms with neuroimaging in the diagnosis of MDD or classification of MDD patients from healthy controls [25-30]. One study conducted by Abou-Warda, H. et al. (2016) used RF with impute missing values learner on datasets to enhance the diagnostic system of mental disorders [25]. Although the experiments yielded accuracy results of at least 90%, neuroimaging data was omitted [25]. Another study by Cacheda, F. et al. (2019) analyzed data from social media networks to examine methods of early detection of MDD based on RF [26]. Among other researches, RF has been applied on neuroimaging data to predict neurodegenerative diseases such as Alzheimer's disease [27, 28], classify patients with alcohol use disorder from healthy controls [29], and predict treatment response in depression [30]. Nevertheless, no study regarding RF in diagnosis or classifying MDD using neuroimaging data has been found [25-30].

Out of the methods discussed, deep learning (DL) has been the latest development [31]. Due to enhanced computing power with current graphics processing units, the availability of big data, and the creation of novel algorithms to train deep models, DL has achieved unprecedented improvements in most artificial intelligence research areas, especially computer vision which prompted the use of DL in medical analysis to explore translational biomarkers in the brain [31]. For example, after building EEG-based diagnosis model using through deep convolutional neural network (CNN) for classifying MDD patients from healthy controls, Uyulan, C. et al. (2020) was able to reveal that the higher average delta amplitude in MDD than that of healthy control subjects may indicate a biomarker for MDD, and proposed that the methodology can be adapted to computer-assisted diagnosis of MDD to validate clinical diagnosis [32]. However, Safayari, A., & Bolhasani, H. (2021) regarded that these models could pose some implementation challenges to clinical environments due to complexity and novelty [33]. Among similar studies, the lack of sufficient data to improve or evaluate the accuracy of the DL-based methods is one the main barriers to clinical utility [33].

MATERIALS AND METHODS

This section summarizes the general framework undertook by researchers during the investigative process to classify MDD patients from non-MDD participants. The beginning of the methodology often covers the screening procedures

of participants for experimental researches and/or articles for reviews and references. After the acquisition of volunteers, the next stage involves building and evaluating machine learning models in performing in accordance to the objectives established by the researchers.

Screening Methods

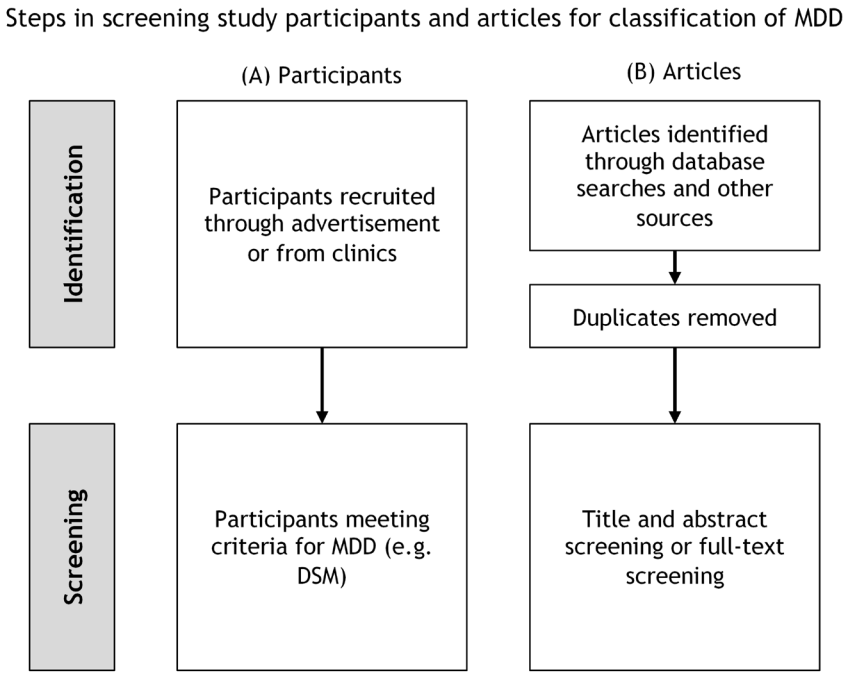

Figure 2. Visual summary of each screening step based on PRISMA screening method diagram [34]. (A) Screening of study participants or research subjects. (B) Screening of articles for literature reviews.

Figure 2A summarizes each screening step of participants for the study. Participants meeting the Diagnostic and Statistical Manual of Mental Disorders (DSM) criteria (or any other equivalent assessment) for MDD were recruited through advertisement or from local mood disorders clinics. Structured clinical interviews, such as the Composite International Diagnostic Interview (CIDI) or Structured Clinical Interview for DSM-IV Axis 1 Disorders, were conducted to confirm the diagnosis of MDD and the absence of any other mental disorder. Recruited healthy controls or patients with other mood disorders also went through similar structured interviews. Depression severity may be measured with the aid of clinician-administered depression assessment scale, such as the Hamilton Depression Rating Scale (HDRS), to assist in the diagnosis or grouping [32, 35, 36].

Figure 2B shows the general procedure for screening articles. Studies focusing on classification between individuals with MDD and healthy controls (or other disorders) using machine learning methods were identified using searches in database and reference lists. After removing duplicates, the selected articles went through title and abstract screening, and then full-text screening to exclude articles that, for example, reported predictions without classifiers [18].

Machine Learning Process

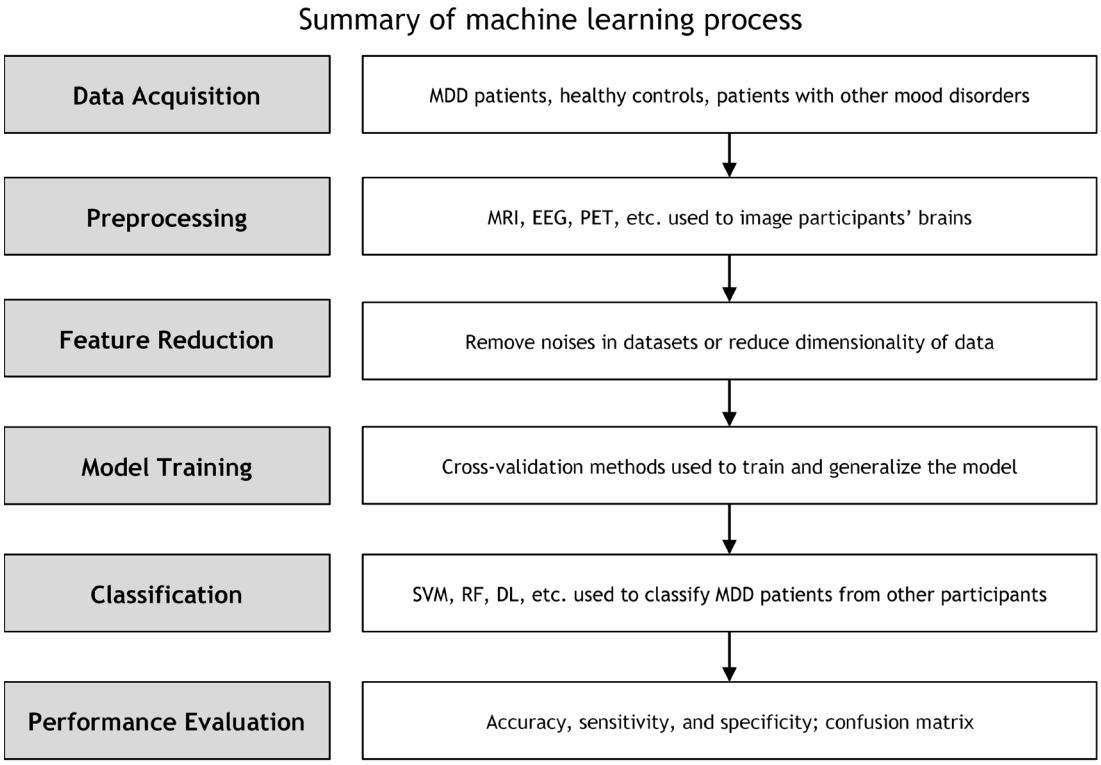

Figure 3. Summary of data processing steps in machine learning to classify MDD.

Machine learning (ML) consists of a set of methods that can detect patterns in data, and then use them to develop prediction models to make accurate predictions about new data under uncertainty. Depending on the data, two types of ML can be employed: supervised learning is performed when all data is labeled, and unsupervised learning when all data is unlabeled. Supervised learning can be further categorized as classification-based methods, which classify the data by discrete labels, or regression-based methods, which fit data to a continuous function. For unsupervised learning, the methods are generally categorized as clustering methods, which group data into clusters based on underlying similarities [19]. Figure 3 summarizes each step of data processing in machine learning.

Data acquisition and preprocessing involve the use of neuroimaging techniques to study participants' brains in non-invasive ways. Most researches focus on magnetic resonance imaging (MRI) modalities to obtain data for training predictive models, but there are researches that use other methods such as positron emission tomography (PET) and electroencephalography (EEG) to study brain structure and function. The most common MRI techniques to observe brain structure include T1-weighted imaging, T2-weighted imaging, and Diffusion Tensor Imaging (DTI). For the study of brain function, functional MRI (fMRI) is generally used and can be further characterized into resting-state or task-based fMRI [14, 18, 22, 35].

After obtaining brain images, feature reduction methods are used to reduce the number of features in the high-dimensional data to a limited number of discriminant features for helping in creating a more accurate classification model. Feature reduction methods are primarily categorized into feature selection and feature extraction. Feature selection is performed when supervised ML methods select the most relevant features using labels of input data to reduce noise, while feature extraction is performed when underlying patterns are selected from input features to reduce

the dimensionality of the input data while retaining some discriminative properties. The most commonly used methods in past studies fall into the supervised feature selection methods [18, 22].

Model training for a supervised learning approach involves optimizing a model using labeled data to define a parameterized function. The parameters are optimized to maximize discrimination between two groups. After performing feature reduction, cross-validation is used on the resulting dataset to provide the learning method with data for training the prediction model and generalizing the training process. This technique first divides the data into test dataset and training dataset. Then, the ML method is applied to the training dataset to create an estimated prediction model. This model is subsequently iterated on different groups of test data to compute appropriate validation measures for assessing the generalization ability of the model to avoid overfitting. Finally, the validation measure values from all iterations are averaged to evaluate the overall performance of the learning method [18, 22].

In the classification stage, the trained model is used to predict the label for new input data. The data are preprocessed the same way and the same feature reduction method is also applied with optimized parameters acquired from model training. In some cases where new data are not available due to limited sample size, a nested cross-validation approach can be applied to estimate the performance instead. The most commonly used classifier in past studies is support vector machine (SVM) because of its effectiveness in neuroimaging involving small sample groups [18, 22].

Finally, in the performance evaluation phase, one of the methods to describe the performance of classification-based algorithms is by calculating the accuracy, sensitivity, and specificity. Accuracy is a general metric used to measure the correctness of data points correctly identified by the learning method. Sensitivity evaluates the ability to correctly identify the proportion of true positives (such as the percentage of patients identified as MDD) while specificity evaluates the ability to correctly identify the proportion of true negatives (such as the percentage of healthy people identified as healthy control). Another method is to use charts, such as the receiver operating characteristic (ROC) curve to illustrate the overall aptitude (which is usually summarized by the area under the curve) or a confusion matrix to provide information for computing additional metrics such as precision [18].

CONCLUSION

This study concentrated on reviewing the diagnosis of major depressive disorder (MDD) by machine learning algorithms using neuroimaging techniques. The integration of machine learning methods with neuroimaging data provides unprecedented opportunities to deepen the analysis of depression and enhance the current clinical approach to diagnosis. Although many models exhibit promising results, their incorporation to neuroimaging is still largely exploratory: the lack of sufficient data/samples and the need to further evaluate its accuracy for clinical practice pose barriers to successful clinical application [22, 33, 35]. One study proposes that the small sample size can be overcome by standardizing the acquisition and processing parameters throughout the neuroimaging research community to allow more useful data pooling [22], while unreliable accuracy and overfitting can be solved by experimenting with different machine learning algorithms, feature selection methods, and neuroimaging techniques [18, 33, 35]. Therefore, further investigation is crucial to determine an optimal approach to MDD diagnosis for designing a model that is compatible with the clinical environment.

REFERENCES

1. American Psychiatric Association. (2013). Diagnostic and statistical manual of mental disorders (5th ed.). https://doi.org/10.1176/appi.books.9780890425596

2. Bromet, E., Andrade, L. H., Hwang, I., Sampson, N. A., Alonso, J., de Girolamo, G., de Graaf, R., Demyttenaere, K., Hu, C., Iwata, N., Karam, A. N., Kaur, J., Kostyuchenko, S., Lépine, J.-P., Levinson, D., Matschinger, H., Mora, M. E., Browne, M. O., Posada-Villa, J., … Kessler, R. C. (2011). Cross-national epidemiology of DSM-IV major depressive episode. BMC Medicine, 9(1). https://doi.org/10.1186/1741-7015-9-90

3. Vos, T., Barber, R. M., Bell, B., Bertozzi-Villa, A., Biryukov, S., Bolliger, I., Charlson, F., Davis, A., Degenhardt, L., Dicker, D., Duan, L., Erskine, H., Feigin, V. L., Ferrari, A. J., Fitzmaurice, C., Fleming, T., Graetz, N., Guinovart, C., Haagsma, J., … Murray, C. J. L. (2015). Global, regional, and national incidence, prevalence, and years lived with disability for 301 acute and chronic diseases and injuries in 188 countries, 1990–2013: A systematic analysis for the global burden of disease study 2013. The Lancet, 386(9995), 743–800. https://doi.org/10.1016/s0140-6736(15)60692-4

4. Sullivan, P. F., Neale, M. C., & Kendler, K. S. (2000). Genetic epidemiology of major depression: review and meta-analysis. The American journal of psychiatry, 157(10), 1552–1562. https://doi.org/10.1176/appi.ajp.157.10.1552

5. Kendler, K. S., Gatz, M., Gardner, C. O., & Pedersen, N. L. (2006). A Swedish national twin study of lifetime major depression. The American journal of psychiatry, 163(1), 109–114. https://doi.org/10.1176/appi.ajp.163.1.109

6. Li, M., D'Arcy, C., & Meng, X. (2016). Maltreatment in childhood substantially increases the risk of adult depression and anxiety in prospective cohort studies: systematic review, meta-analysis, and proportional attributable fractions. Psychological medicine, 46(4), 717–730. https://doi.org/10.1017/S0033291715002743

7. Pandya, M., Altinay, M., Malone, D. A., Jr, & Anand, A. (2012). Where in the brain is depression?. Current psychiatry reports, 14(6), 634–642. https://doi.org/10.1007/s11920-012-0322-7

8. Smith, K. M., Renshaw, P. F., & Bilello, J. (2013). The diagnosis of depression: current and emerging methods. Comprehensive psychiatry, 54(1), 1–6. https://doi.org/10.1016/j.comppsych.2012.06.006

9. Uher, R., Payne, J. L., Pavlova, B., & Perlis, R. H. (2013). Major depressive disorder in DSM-5: Implications for clinical practice and research of changes from DSM-IV. Depression and Anxiety, 31(6), 459–471. https://doi.org/10.1002/da.22217

10. Hamilton, M. (1960). A rating scale for depression. Journal of Neurology, Neurosurgery & Psychiatry, 23(1), 56–62. https://doi.org/10.1136/jnnp.23.1.56

11. Kovacs, M., Obrosky, S., & George, C. (2016). The course of major depressive disorder from childhood to young adulthood: Recovery and recurrence in a longitudinal observational study. Journal of affective disorders, 203, 374–381. https://doi.org/10.1016/j.jad.2016.05.042

12. Cuijpers, P., van Straten, A., Andersson, G., & van Oppen, P. (2008). Psychotherapy for depression in adults: A meta-analysis of comparative outcome studies. Journal of Consulting and Clinical Psychology, 76(6), 909–922. https://doi.org/10.1037/a0013075

13. Shelton C. I. (2004). Long-term management of major depressive disorder: are differences among antidepressant treatments meaningful?. The Journal of clinical psychiatry, 65 Suppl 17, 29–33.

14. Dunlop, B. W., & Mayberg, H. S. (2017). Neuroimaging Advances for Depression. Cerebrum: the Dana forum on brain science, 2017, cer-16-17.

15. Friston, K. J., Holmes, A. P., Worsley, K. J., Poline, J.-P., Frith, C. D., & Frackowiak, R. S. (1994). Statistical parametric maps in functional imaging: A general linear approach. Human Brain Mapping, 2(4), 189–210. https://doi.org/10.1002/hbm.460020402

16. Davatzikos, C. (2004). Why voxel-based morphometric analysis should be used with great caution when Characterizing Group differences. NeuroImage, 23(1), 17–20. https://doi.org/10.1016/j.neuroimage.2004.05.010

17. Yoo, K., Rosenberg, M. D., Noble, S., Scheinost, D., Constable, R. T., & Chun, M. M. (2019). Multivariate approaches improve the reliability and validity of functional connectivity and prediction of individual behaviors. NeuroImage, 197, 212–223. https://doi.org/10.1016/j.neuroimage.2019.04.060

18. Gao, S., Calhoun, V. D., & Sui, J. (2018). Machine learning in major depression: From classification to treatment outcome prediction. CNS neuroscience & therapeutics, 24(11), 1037–1052. https://doi.org/10.1111/cns.13048

19. Murphy, K. P. (2012). Machine learning: A probabilistic perspective. Cambridge, MA: MIT Press.

20. Wernick, M. N., Yang, Y., Brankov, J. G., Yourganov, G., & Strother, S. C. (2010). Machine Learning in Medical Imaging. IEEE signal processing magazine, 27(4), 25–38. https://doi.org/10.1109/MSP.2010.936730

21. Lao, Z., Shen, D., Xue, Z., Karacali, B., Resnick, S. M., & Davatzikos, C. (2004). Morphological classification of brains via high-dimensional shape transformations and machine learning methods. NeuroImage, 21(1), 46–57. https://doi.org/10.1016/j.neuroimage.2003.09.027

22. Patel, M. J., Khalaf, A., & Aizenstein, H. J. (2016). Studying depression using imaging and Machine Learning Methods. NeuroImage: Clinical, 10, 115–123. https://doi.org/10.1016/j.nicl.2015.11.003

23. Hsu, C. W., Chang, C. C., & Lin, C. J. (2003). A practical guide to support vector classification.

24. Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5–32. https://doi.org/10.1023/a:1010933404324

25. Abou-Warda, H., Belal, N. A., El-Sonbaty, Y., & Darwish, S. (2016). A random forest model for Mental Disorders Diagnostic Systems. Advances in Intelligent Systems and Computing, 670–680. https://doi.org/10.1007/978-3-319-48308-5_64

26. Cacheda, F., Fernandez, D., Novoa, F. J., & Carneiro, V. (2019). Early detection of depression: Social network analysis and Random Forest Techniques. Journal of Medical Internet Research, 21(6). https://doi.org/10.2196/12554

27. Velazquez, M., & Lee, Y. (2021). Random forest model for feature-based Alzheimer's disease conversion prediction from early mild cognitive impairment subjects. PLOS ONE, 16(4). https://doi.org/10.1371/journal.pone.0244773

28. Sarica, A., Cerasa, A., & Quattrone, A. (2017). Random Forest algorithm for the classification of neuroimaging data in Alzheimer's disease: A systematic review. Frontiers in Aging Neuroscience, 9. https://doi.org/10.3389/fnagi.2017.00329

29. Kamarajan, C., Ardekani, B. A., Pandey, A. K., Kinreich, S., Pandey, G., Chorlian, D. B., Meyers, J. L., Zhang, J., Bermudez, E., Stimus, A. T., & Porjesz, B. (2020). Random Forest classification of alcohol use disorder using fmri functional connectivity, neuropsychological functioning, and impulsivity measures. Brain Sciences, 10(2), 115. https://doi.org/10.3390/brainsci10020115

30. Wade, B. S., Joshi, S. H., Pirnia, T., Leaver, A. M., Woods, R. P., Thompson, P. M., Espinoza, R., & Narr, K. L. (2015). Random Forest Classification of Depression Status Based On Subcortical Brain Morphometry Following Electroconvulsive Therapy. Proceedings. IEEE International Symposium on Biomedical Imaging, 2015, 92–96. https://doi.org/10.1109/ISBI.2015.7163824

31. Lee, J.-G., Jun, S., Cho, Y.-W., Lee, H., Kim, G. B., Seo, J. B., & Kim, N. (2017). Deep Learning in Medical Imaging: General overview. Korean Journal of Radiology, 18(4), 570. https://doi.org/10.3348/kjr.2017.18.4.570

32. Uyulan, C., Ergüzel, T. T., Unubol, H., Cebi, M., Sayar, G. H., Nezhad Asad, M., & Tarhan, N. (2020). Major depressive disorder classification based on different convolutional neural network models: Deep Learning Approach. Clinical EEG and Neuroscience, 52(1), 38–51. https://doi.org/10.1177/1550059420916634

33. Safayari, A., & Bolhasani, H. (2021). Depression diagnosis by deep learning using EEG Signals: A systematic review. Medicine in Novel Technology and Devices, 12, 100102. https://doi.org/10.1016/j.medntd.2021.100102

34. Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: The Prisma statement. PLoS Medicine, 6(7). https://doi.org/10.1371/journal.pmed.1000097

35. Ramasubbu, R., Brown, M. R. G., Cortese, F., Gaxiola, I., Goodyear, B., Greenshaw, A. J., Dursun, S. M., & Greiner, R. (2016). Accuracy of automated classification of major depressive disorder as a function of symptom severity. NeuroImage: Clinical, 12, 320–331. https://doi.org/10.1016/j.nicl.2016.07.012

36. Khodayari-Rostamabad, A., Reilly, J. P., Hasey, G. M., de Bruin, H., & MacCrimmon, D. J. (2013). A machine learning approach using EEG data to predict response to SSRI treatment for major depressive disorder. Clinical Neurophysiology, 124(10), 1975–1985. https://doi.org/10.1016/j.clinph.2013.04.010